Computation of convective kernels growing rate

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Introduction

Most of satellite based rainfall estimation methods merge polar orbiting microwave data with geostationary infrared images. The geostationary satellite is mainly used to complement in time and space microwave estimator on a pixel basis but less for dynamic cloud properties retrieval. Yet it is well known that the most intense rainfall intensity is associated with a growing phase of convective kernels and a proper assessment of this growing rate could supply valuable information for these estimations methods.

Although automatic cloud tracking methods are used on an operational basis, growing rates are usually estimated as a temperature difference between two successive images without references to spatial structures. Going beyond a cooling rate to a kernel surface variation indicator requires a proper management of clusters splitting and merging. But, most of all, kernels identification is a key issue. Obviously a Mesoscale Convective System (MCS) is not homogeneous as it can get at the same time expanding and decaying cells.

Our basic input information will be a rainfall probability function which is produced from geostationary satellite. This function can be estimated by a simple histogram matching method with microwave data or by a more sophisticated neural network estimator. In this document we will first describe a general heritage algorithm and then discuss its implementation for growing rate assessment.

Description of heritage process

To support both deterministic and probabilistic convective kernel delineation we consider functions from the geographic space (quoted XxY). A fuzzy partition "A" of our space is a set of functions f_a ($a \in A$) satisfying the two properties for each point (x,y):

$$f_a(x,y) \in \{0,1\} \qquad (1)$$

$$\sum_A f_a(x,y) \in \{0,1\} \qquad (2)$$

Let f_a ($a \in A$) and f_b ($b \in B$) fuzzy partitions extracted from two successive images, then h_a the heir of f_a is defined by:

$$h_a(x,y) = \Sigma_{b\in B}\, \lambda_{ab}\, f_b(x,y) \qquad (3)$$

where

$$\lambda_{ab} = Sab \,/\, \Sigma_{a'\in A} Sa'b \qquad (4)$$

and

$$Sab = \iint_{XY} f_a(x,y) f_b(x,y)\, dxdy \quad (5)$$

If equation 4 denominator is null, the corresponding coefficient is set to zero.

The growing rate of fuzzy cluster a is then:

$$\iint_{XY} h_a(x,y)dxdy \,/\, \iint_{XY} f_a(x,y)dxdy \quad (6)$$

It can be verified that h_a ($a \in A$) functions satisfy conditions 1 and 2 and are therefore a fuzzy partition. Should all the functions be deterministic (getting as value only 0 or 1), then f_a (resp. f_b) can be considered as the a (resp. b) cluster indicator function and Sab as the intersection surface of clusters a and b. As the heritage is ponderated by intersection surface, it is not necessary to suppress little clusters by a threshold on surface.

An important property of this process is that the heir of $f_a+f_{a'}$ is $h_a+h_{a'}$ and so it is not sensitive to cluster merging.

The formula 3 is a matrix product and direct computation is easy as long as the number of fuzzy partition elements is not to high. The set of coefficients λ_{ab} is called the transition matrix from A to B.

Actual implementation and results

The space is first segmented by a watershed algorithm applied to the probability function. The local maxima of rainfall probability are assimilated to pits. The fuzzy partition is the product of the generated set indicator functions by the rainfall probability. Using a non uniform measurement is important to suppress the non significant low probability area.

A direct watershed process on the rainfall probability field should produce a thin segmentation. This could increase the computing time and mitigate the efficiency of the heritage process. As this algorithm is based on overlapping area, the mean cloud motions have to be small in front of the cells area size. So a prior step is to smooth the probability function by a median filter. As heuristic, we suggest to set the filter size to the order of the average MCS displacement during an interslot lag.

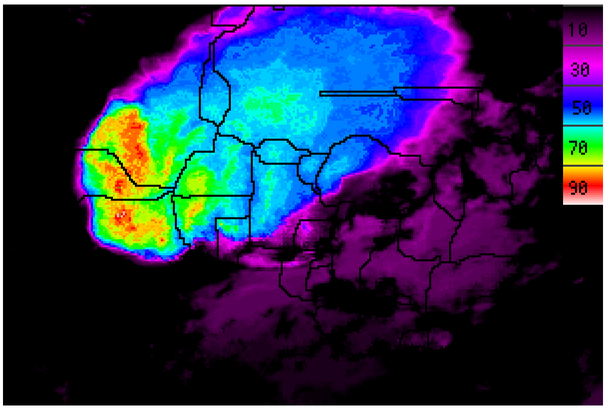

Figure 1: Watershed segmentation 2005/30/07 00:15. overlayed with rainfall probability (%)

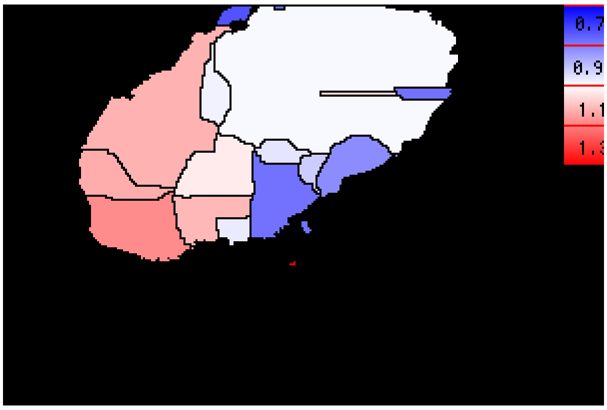

Figure 3: Growing rate ftom 2005/30/07 00:15 to 0:30

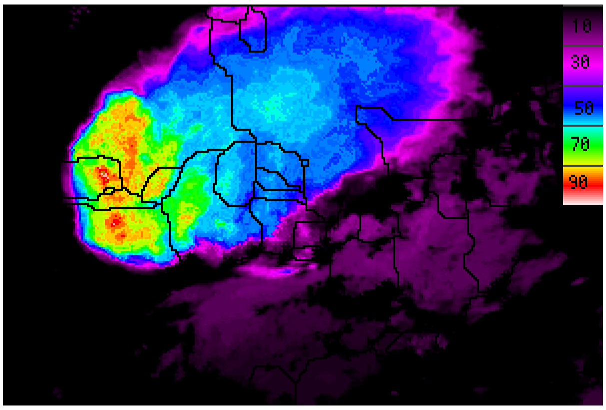

Figure 2: Watershed segmentation 2005/30/27 00:30

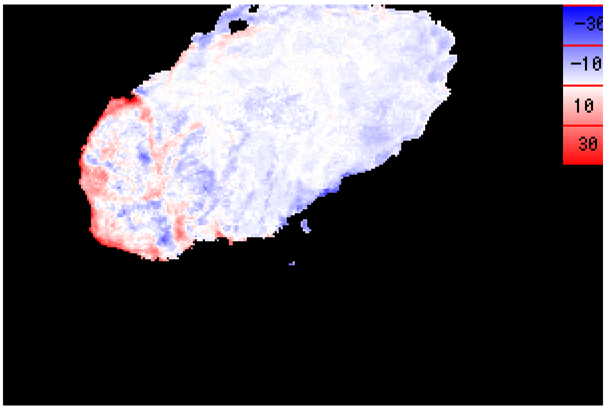

Figure 4: Rainfall probability difference

Figures 1 and 2 display rainfall probability on two successive images of a sahelian convective system. On this system moving a south-west direction, the most active cells are in front whereas the rear part shows a smooth probability gradient. The boundaries produced by the watershed algorithm are linked to local maxima and are rather unstable. So, the follow up of cells surface requires a much more sophisticated heritage method than automatic cloud tracking which relies on clearly separated markers.

The resulting growing rate estimator (figure 3) has been masked to suppress the low rainfall probability area. As expected the highest values are located on the active front of the system. A comparison with a simple difference of rainfall probability (figure 4) shows a good general agreement. But at a finer scale, cooling rate is more associated with cloud motion than with cells size change and its internal variability does not appears as relevant.

Conclusion

A new method has been described to retrieve convective kernel growing rate. At an event scale, it looks as more efficient than the cooling rate usually computed. However the computational burden associated with watershed algorithm makes this method much heavier to run on long series of data. To speed up the process the watershed delineation could be replaced by an adaptative threshold and a simple labelling.

An open issue should be to assess at which aggregation scale these methods give similar results and which biases are introduced. The TRMM/PR will be used as a reference dataset to investigate statistical relation with rainfall intensity.